

# LAND COVER CLASSIFICATION OF BOREAS MODELING GRID USING AIRSAR IMAGES

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## ABSTRACT

*Mapping forest types in the boreal ecosystem is an integrated part of any modeling exercise of biogeophysical processes characterizing the interaction of forest with the atmosphere. In this paper we report the results of the land cover classification of the SAR data acquired during the BOREAS (Boreal Ecosystem Atmospheric Study) intensive field campaigns over the modeling sub grid of the southern study area in Saskatchewan, Canada. A Bayesian maximum-a-posteriori classifier has been applied on the NASA/JPL AIRSAR images covering the region during the peak of the growing season in July 1994. The approach is supervised in the sense that a combination of field data and existing land cover maps are used to develop training areas for the desired classes. The images acquired were first radiometrically and absolutely calibrated, the incidence angle effect in airborne images was corrected to an acceptable accuracy, and the images were used in a mosaic form and georeferenced with an existing land cover map for validation purposes. The results show that SAR images can be classified into dominant forest types such as jack pine, black spruce, trembling aspen, clearing, open water, and three categories of mixed stands with better than 90% accuracy. The mixed species stands such as jack pine and black spruce are separated with 98% accuracy, but the accuracy of mixed coniferous and deciduous stands suffers from confusing factors such as varying species composition, surface moisture and understory effects. To satisfy the requirements of process models, the number of cover types was reduced from 8 to 5 general classes of conifer wet, conifer dry, mixed deciduous, disturbed, and open water. Reduction of class's improved the overall accuracy of the classification over the entire region from 77% to 92%.*

## INTRODUCTION

One of the major challenges of developing Earth Systems Process models both in global and regional scales is the accurate representation of the terrestrial vegetation. These process models work at a variety of spatial scales ranging from several meters to kilometers. Depending on the application of the processes and their scales, the definition of categories of vegetation types may change. For example, for land-atmosphere models such as RATS, eighteen general land cover classifications are defined which are often derived from maps, atlases and national databases (Dickenson, 1994). This procedure assumes homogeneous vegetation classes over a grid square (e.g.  $5^{\circ}$  by  $5^{\circ}$ ). Over more heterogeneous land surfaces, net scale process models are used to improve understanding of biogeochemical and physiological relationships. The availability of high resolution land cover maps can improve the parameterization of landscape to functionally different strata for both global and regional scale modeling. Currently, there are several approaches under investigation for statistically aggregate the high resolution maps derived from remote sensing techniques to a desired process model grid scale [Hall et al., 1994]. These techniques are primarily focused on exploiting optical remote sensing data such as AVHRR and Landsat [Sellers et al., 1994].

As a complement to optical remote sensing techniques, land cover maps derived from multipolarization, multifrequency synthetic aperture radar (SAR) systems present an important tool to terrestrial ecologists and process modelers. Independence of SAR data of solar irradiance and cloud cover is one significant reason for using this technique for land cover classification, especially in northern latitude of boreal forest and tropical rainforest where the acquisition of optical data is hindered by frequent cloud cover and fire smoke. In addition, the sensitivity of the radar signal to moisture content and structural properties of vegetation may separate forest types particularly when optical sensors are saturated over dense vegetation. Several studies, using a variety of classification approaches, have used SAR images for land cover type classification in forest regions [Rignot et al., 1994, Ranson and Sun, 1994, Dobson et al., 1994, Cimino et al., 1986]. The application of these high resolution maps in process models has not been thoroughly examined. Studies such as in Bonan (1993) that the SAR derived land cover map over the boreal forest of interior Alaska was used to improve the estimation of forest assimilation are rare.

Before we delve further into the discussion of the methodology and the results, it is important to articulate the underlying rationale for this study. The classification of the land cover are used to address the specific requirements of the 3DRAS modeling activities. In other words, separate functionally important land cover types for

modeling, the exchange of trace gases between the land surface and the atmosphere is the ultimate goal of the study. The area has been under intensive study during the BOREAS (Boreal Ecosystem Atmosphere Study) project for its important role in biogeochemical cycles between land and atmosphere at northern latitude [Sellers et al., 1995]. The land cover types in this region can be characterized by only a few dominant tree species. For example, the separability of conifer and deciduous stands and the dry and wet conditions in this region are important for estimating the rates of photosynthesis, respiration, carbon assimilation and nitrogen concentration. Therefore, the process of classification using SAR imagery is first to illustrate the capability of the instrument to identify these classes and secondly to show the spatial pattern of these classes over a region used for ecosystem processing models. In this study we discuss the application of SAR data for mapping of forest types in the BOREAS study area. A supervised classification approach using a *maximum-a-posteriori* Bayesian classifier is applied on the three-frequency polar metric data. A RSAR data to identify 8 classes. Classification accuracies are computer based on first the areas used for training, the classifier, then over several homogeneous sites examined during the field observation, and finally by comparing the results with a digital vegetation map assembled from infrared aerial photo interpretation performed in 1984.

## BOREAL ECOSYSTEM

The Boreal Ecosystem Atmosphere Study (BOREAS) is a cooperative field experiment integrating land surface climatology, tropospheric chemistry, and terrestrial ecology. In general, the experiment was designed to extend the findings of HFE over grass prairie to one of the Earth's largest and complex biomes, the boreal forest, where coniferous species dominate. The biome has upland forests, extensive wetlands, some deciduous species, many lakes, and is a major storehouse of organic carbon, mostly in the soil [BOREAS Science Steering Committee, EOS, 1990]. Among the major objectives of the experiment, improving understanding of the processes that govern the exchange of energy, water, heat, carbon, and trace gases between boreal forest ecosystem and atmosphere, and developing and validating remote sensing techniques to transfer the knowledge of these processes from local to regional scales are of great importance. One relevant scientific issue is the sensitivity of the boreal forest biome to changes in physical climate and *vice versa*. Therefore, mapping the cover types and the changes in the land use and the species composition in the region has also a long term climatological application.

### *Site Description:*

The focus of this paper is the BOREAS southern study area (SSA) which covers an area about 130 km in the east-west direction and 90 km from north to south (Figure 1). The southern boundary is located approximately 40 km north of the town of Prince Albert, Saskatchewan, Canada. The SSA topography is gentle, with local elevations ranging from 550-730 m. Soils range from gray wooded to degraded black and are classified as brunisolic, gleysolic, chenzemic, luvisolic and organic soil orders. Glacial deposits vary in thickness from 100-1000 m on the top of the Cretaceous Age bedrock. The western part of the SSA is in the Prince Albert National Park (PANP) and the eastern region falls within and around the Narrows Hills Provincial Forest.

The SSA is near the southern limit of the boreal forest and the transition to natural prairie grassland and agricultural lands occurs 15 km to the southeast. The image data discussed in this paper is located in the east of PANP in the area of the Narrows Hills Provincial Park. The image area also coincides with the BOREAS modeling grid (50 km x 50 km) used mainly for verifying remote sensing algorithms and ecosystem modeling results. The vegetation in this area is classified as mixed boreal forest. On well drained and sandy soil the predominant species is jack pine (*Pinus banksiana*). Poorly drained sites support black spruce (*Picea mariana*). Mixed stands of aspen (*Populus tremuloides*), balsam poplar (*Populus balsamifera*) and white spruce (*Picea glauca*). Localized logging for paper pulp and fence posts is common along Highway 106, 120 and Harding Road (see Fig. 1). The poorly drained areas throughout the study area, bogs support black spruce with tamarack (*Larix laricina*). The fen areas are composed mostly of sedge (*Carex spp.*) vegetation with discontinuous cover of tamarack or swamp birch (*Betula pumila*). The north-east portion of the study area encompasses a portion of the fishing lakes burn which occurred in 1977 and 1978. Stands of small (<5 cm) jack pine regrowth now cover most of the burn areas.

Major land-cover types are identified according to the needs of the BOREAS scientific applications. These land-cover types are chosen based on their dominant species, canopy closure, soil organic properties, and their roles in determining the physics of the interaction of land surface and atmosphere. The land-cover categories consist of dry conifers (e.g. jack pine), wet conifers (e.g. black spruce), deciduous (trembling aspen), clear cut, open water (lakes and river), brushland, treed muskeg, mixed coniferous and deciduous trees, and regrowth (e.g. young jack pine). Between summer of 1993 and fall of 1994, forest stands of major land cover were sampled to measure tree species composition, stand geometry, biomass density, and several other forest canopy attributes. The field data collection were performed by having several applications in mind, and are

available for all the flux tower and auxiliary sites. The flux tower sites are mainly single species stands.

In addition, there exists a digital vegetation map of SSA that has been assembled from 1:12,500 scale infrared aerial photography and field reconnaissance notes in 1984. This vegetation map has been verified on the ground but no accuracies are provided. The map consists of more 40 different classes, that regrouped to simplify the representation of vegetation types for dominant classes (Figure 2). Since this map was acquired in 1984, it is not entirely accurate today. The map does not reflect recent changes due to tree logging, regrowth and transformation of treed muskeg to predominantly black spruce stands.

## AIRSAR Data

The JPL airborne synthetic aperture radar (AIRSAR) was flown aboard the NASA DC-8 during all the intensive field campaigns (IFC) in summer of 1993, April 1994 during the thaw period of the boreal forest, and in summer and fall of 1994. The AIRSAR operates at three frequency bands, P-band (68cm wavelength), L-band (24cm), and C-band (5.6cm) with fully polarimetric capability. The incidence angle of the radar varied between approximately  $20^{\circ}$  and  $60^{\circ}$ . 'P-HIL' radar data used for land-cover classification were acquired in July 21, 1994 and processed in synoptic mode (50km swath). We have chosen this date to avoid possible errors in classification due to the partially frozen condition during the thaw period and leaf-off condition during the fall season. All synoptic 1110 (1C), strips of radar images are processed with fixed radar parameters along the swath and without the aircraft motion compensation. These images often suffer from accurate calibration and radiometric correction. However, it is the appropriate mode for large area mapping. We have used images from several parallel flight lines in a mosaic mode to create larger area coverage over the modeling grid. The calibration, radiometric correction, and mosaic of the images were performed in several steps as follows:

### *Image Calibration:*

In this study we have made use of synoptic SAR images which were acquired with parallel flight lines in a "race-track" trajectory. The synoptic images have larger coverage (approximately 50 km) but only three polarizations. These images are often processed for the purpose of surveying the area and are not absolutely calibrated. We have processed a total of 15 synoptic images to cover all the bands of polarizations of the

AIRSAR system. Calibration of images are performed by using fully polarimetric calibrated frame images processed over a portion of the synoptic images. Absolute calibration constants were obtained by computing the ratios of backscattering coefficients from identical areas from both images and applying the calibration constants to all synoptic images. When compared with frame images, the synoptic images were absolutely calibrated with less than 0.1 dB error for all polarization channels. The frame images were calibrated both internally and externally using data collected over an array of corner reflectors deployed over the Rosemond dry lake calibration site in California before and after the AIRSAR campaign. After the absolute calibration, the images were resampled to ground range to remove the distortions in the near range and far range pixels.

### *Incidence Angle Correction:*

One of the disadvantages of airborne SAR data, when used for land-cover classification, is the variation of the incidence angle along the range lines across the image (20°-60°). Consequently, areas with similar land-cover types produce different backscatter signatures if they are imaged at different incidence angles and depending on the scene characteristics, the variation of the backscatter signature along each range line may be different. These effects can cause inaccuracies in a consistent class separation over the entire image. Correction of the image for incidence angle effects, therefore, becomes a necessary but impossible task to accomplish exactly. To have an optimal correction for incidence angle effects, several approaches have been suggested. For example, Yuch et al, (1988) normalized the SAR data by the total power. This technique eliminated most of the incidence angle effects but at the same time changed some of the information in SAR backscatter signatures. The resulting normalized images were not able to discriminate all classes. Another method was proposed by Sader (1987) where homogeneous areas of the same types were chosen along the range line and the total image was calibrated such that these areas had equal backscattering signatures. This technique will not work in areas with complex land-cover types. Rignot and Drinkwater (1993) removed this effect in classifying sea ice types in airborne imagery by first segmenting the image along the range line, performing range dependent clustering of the image, regrouping the clusters and employing a supervised classification to produce self-consistent classes across the image scene. However, their technique requires that similar class types are represented in each segment of the image. Over complex land cover types, sometimes, only a limited number of classes is present over each range segment causing difficulty in regrouping the clusters and removing the range dependent effects.

Ranson and Sun, (1994) used A11<SA1< images over forested land surfaces, selected a portion of each image line within sapwood areas, calculated the mean and standard deviation of these pixels, and discarded all pixels falling outside of  $\pm 2$  standard deviations. The remaining pixels were used to estimate the mean values at each image row, then a linear regression was used to estimate the calibration ratio for each line, and subsequently, the entire image was calibrated using these ratios. When employing this technique, it was found that the linear regression method did not always compensate for the inhomogeneous scene characteristics along the range line.

The synoptic images used in this study were corrected for incidence angle variations with a slightly different technique than Ranson and Sun (1994). In this approach, we plotted the incidence angle variations for each range line, then a nonlinear regression in conjunction with a cubic spline smoothing algorithm was used to estimate the general behavior of the incidence angle variations along each range line. The regression curve was then normalized by the mean backscattering coefficient of the range line and then used to correct for the incidence angle effects of that range line. The entire image was then corrected line by line.

### *Image Mosaic.*

After calibration and incidence angle correction, the images from each frequency band and polarization were used in tandem to generate a mosaic image over almost the entire modeling sub-grid. Figure 3 shows a color composite of the mosaic image at P-band (red: P-HH, green: P-HV, blue: P-VV). Since the images were acquired from flight lines with the same heading, they also had an area of overlap with adjacent images. A linear feathering technique was then employed to remove the tonal inconsistencies that existed at the areas of overlap. In some areas where incidence angle effects were not optimally corrected, the feathering technique guaranteed further smoothing at the edges of images. If the overlapping regions were near the lakes where there was a dramatic change in the radar backscatter signature, incidence angle effects could not be totally removed and the edge effects were still obvious in the mosaic image.

## CLASSIFICATION METHODOLOGY

When designing a classifier, it is important to define the mathematical basis of the classifier and at the same time to distinguish between the supervised and unsupervised learning procedures within the classifier. Here, we make use of a *maximum-a-posteriori*

(MAP) Bayesian classifier developed for multifrequency polarimetric SAR data (Rignot and Chellappa, 1992). The MAP classifier models the SAR amplitudes as circular Gaussian distribution, which means that textural variations in radar back scatter from surface are not considered to be significant enough to be incorporated into the classification scheme. In this method, the *a priori* distribution of image classes is modeled using a Markov random field. From the models of the *a priori* distribution of classes, a model for the *a posteriori* distribution of the image classes is derived from the SAR image using the Bayes' theorem. The optimal image classification of the SAR data is defined as the one that maximizes the *a posteriori* distribution of classes and is called the maximum *a posteriori* estimate of the image classes.

The MAP method is inherently different and superior than the *maximum likelihood* estimation (MLE) procedure. The *maximum likelihood* methods view the parameters (classes) as quantities whose values are fixed but unknown and the best classification is defined to be the one that maximizes the probability of obtaining the samples actually observed (Duda and Hart, 1973). The MAP classifier views the parameters or classes as random variables with some *a priori* distribution. Iterative observation of the feature space converts this to an *a posteriori* density, thereby revising the decision about the true nature of classes. One of the advantages of this technique, beside its mathematical rigor, is the fact that it is general enough and with minor modification of the feature space can be applied to both optical and SAR images and therefore creating the opportunity for both comparative and synergistic studies.

A number of other classifiers are also available in the literature that have been used successfully but with limited capability for generalization. Among them, Ranson and Sun (1994) used a combination of principle component analysis and MLE to come up with about 80% accuracy over Northern Experimental Forest near 1 lowland, Maine. Pierce et al. (1994) introduced a knowledge-based classifier over a test site in Northern Michigan. This technique strongly depends on the absolute backscatter values (i.e. live.d over training areas and the texture analysis. The use of this technique is dependent on the calibration of the airborne and spaceborne polarimetric data which often suffers from clutter range and atmospheric distortions. Moreover, the speckle filtering and multilooking technique in polarimetric SAR often degrades spatial resolution and information content (both in magnitude and phase) of the data, sometimes in a nonuniform manner across the image and alters the textural information. Therefore, segmentation of the polarimetric SAR data based on knowledge-based techniques appear to be noisy and not typically suitable for practical applications.



The learning procedure for the classifier is supervised in the sense that the state of the nature (class label) is known in advance and training areas are chosen based on *a priori* knowledge of the scene or the visual interpretation of the image. To implement the MAP classifier over the SAR mosaic image we first define the *a priori* distribution of the SAR data for image classes by computing the average covariance matrix over the single training area. We concentrated on 8 categories of training cover: 1) jack pine (JP), 2) black spruce (BS), 3) trembling aspen/mixed (TA/MX), 4) mixed jack pine and aspen (JP/TA), 5) mixed black spruce and jack pine (BS/JP), 6) mixed stands (MX), 7) clear cut, disturbed and nonforest (CC), and 8) open water (OW). For each category, we selected a single large homogeneous stand from the knowledge acquired from field observations and the existing land-cover map. The average covariance matrices are computed for all three frequencies. The use of limited number of training areas ensures a realistic classification accuracy and the extrapolation of the results to the entire image. Here, we used three training areas for jack pine stand depending on the density and age, two black spruce areas from a tower site and mature treed muskeg stand. Table 1, lists the calibrated radar back scattering coefficients, co-polarized phase difference in degrees, and the coefficient of correlation in the linear domain between the complex amplitudes at HH and VV polarizations. The radar characteristics are obtained from the frame images processed over 10 km x 10 km areas within each synoptic image. The forest stands chosen for the training areas were imaged at nearly the same incidence angle, typically around 45° incidence angle, thereby the radar parameters for the image classes are assumed to be independent of the incidence angle. However, the SAR image was classified over its entire angle variations and although the images were corrected for incidence angle variation along the range line, we can still expect some misclassification, particularly near the areas of overlap. Among the training areas, we encountered some difficulty in identifying aspen stands because of their small sizes within the BORFAS modeling grid and their vicinity to mixed stands. As a result, aspen class is labeled TA/MX in order to illustrate the aspen dominated mixed stands.

## RESULTS AND DISCUSSION

The map of forest types using the SAR data is shown in Figure 4. This result is obtained using polarimetric data at P-band and the HH and HV polarizations at L- and C-bands. The choice of the frequency and polarization channels for achieving the optimum classification results was obtained by changing the dimensionality of the classification, or equivalently, reducing the number of elements in the covariance matrix of each pixel that

are used for classification. Consequently, the optimum classification accuracy was obtained by only excluding L- and C-band VV polarizations. In this process, it was also found that the contribution of P-band data was crucial in separating the classes. The reason for this combination is partially due to the calibration and radiometric inaccuracies at higher frequencies. In particular, the C-band VV-polarized synoptic mosaic data suffered from banding in the image and inaccuracies resulted from incidence angle correction. In fact, when a radar channel does not separate two image classes, it adds as a noise source to the classification, and increases the classification probability of error. The combination of polarizations and frequencies used to attain maximum separability differs from a similar technique applied to 11 AIRSAR frame images over Alaskan boreal forest where the highest accuracy was obtained by only L-band and C-band HV polarizations (Rignot et al., 1994). We believe the reason for this difference resides in the poor radiometric accuracy of the synoptic images at high frequencies in our case, and in the P-band interference problem in the data used over the Alaska region.

Classification accuracy for each class is determined by measuring the number of pixels correctly classified into the class divided by the total number of pixels in that class and is illustrated in the form of confusion matrix. In assessing the total classification accuracy we included open water and clear cut, though they are often separated with no difficulty within SAR images. The contribution of each frequency in the total classification was assessed qualitatively when the classifier results were examined during the dimensionality test. The results indicate that the HV polarizations contribute the most for forest type mapping at all frequencies. As shown in Table 1, the HV channels at L-band and P-band show the highest variability over the range of forest types since they are mainly related to the volume scattering within forest canopy and are sensitive to the forest biomass density. Furthermore, over forested areas the HV backscatter is less sensitive to the incidence angle variation and therefore, the channels are less contaminated by the correction errors that may have remained over the image mosaic. The co-polarized backscatter are less variable over different stands, but since the calibration of co-polarized channels are usually better than the cross-polarized channels, their role in separating classes is significant. For example, over low vegetation, clear cut, and open water, the HV-polarized backscatter is very low and the co-polarized backscatter signatures are the primary source for separating these classes.

Table 2 shows the confusion matrix computed from the results of MLE and MAJ classifiers over the training areas with 90 and 96 percent accuracies respectively. For mixed aspen and jack pine (JP/TA) class only 72% of pixels over the training area was classified accurately. The reason for this is the similar average co-polarized backscatter

values at all three bands. In general for mixed stands, the choice of the training areas are poor compared with the mono-species homogeneous stands and as a result the mean backscatter returns for these sites are not very distinctive. Therefore, we expect poor accuracies over TA/MX sites since even in this region, most of the aspen stands are mixed with conifer trees. Jack pine and black spruce stands are classified with 100% and 99% accuracy respectively. P-band and L-band HH polarizations are the main channels for separating these two classes. In jack pine stands, the trees are taller with less foliage and with dry and smooth ground surface, that collectively contribute to high double-bounce return at HH polarization (Moghaddam and Saatchi, 1995). The black spruce stands, on the other hand, have shorter trees, more foliage, and thick and wet moss layer and thus lower returns at HH polarization because of the absorption of the electromagnetic energy by the underlying moss layer.

To examine the ability of the classifier in separating coniferous and deciduous stands, we applied the classifier, without any changes in its current configuration, on an AIRSAR frame image acquired over the aspen tower site in the Prince Albert National Park on the same date. The image covers the area south of Halkett lake and north of dirt road Rt. 240 and is centered at the aspen tower site at almost 45° incidence angle. The area is covered mainly with aspen trees and with small scattered patches of balsam poplar (*Populus balsamifera*) that are similar in structure to aspen. The result of the classification is shown in Figure 5. From the visual interpretation of the map, it appears that the classifier separates the aspen stands with no difficulty. Over the tower site, the classification accuracy reached 100%. This is one of the striking results of the SAR classification because in general, the separation of coniferous and deciduous stands in boreal forests is one of the most challenging problems in any land cover classification. This result also indicates that over homogeneous stands, the structural information of the forest embedded in the SAR backscatter data becomes one of the key discriminates in the forest type classification.

To analyze the accuracy of the SAR derived cover map further, we compared the map with the field data and the existing land cover map (derived from the infrared aerial photography). Table 3 shows the tree species composition of 19 test sites within the modeling grid obtained from actual measurements for each site, the vegetation map, and the SAR map. The ground measurements were conducted during the intensive field campaigns in summer of 1994 and coincide with the time frame the SAR data were acquired. The species composition were measured on small plots within each stand and was not designed to address the species composition at the SAR pixel scale. The vegetation map is almost 10 years old and may be inaccurate because it is based on the

visual interpretation of the aerial photography and dots not include the changes that had occurred since then. However, we have included the map as an extra source for evaluating the accuracy of the SAR map. Moreover, the classifier was used to label each pixel by the dominant forest type and was never intended to estimate the species composition. Nevertheless, by performing this comparison, we will be able to examine the general performance of the classifier and the capability of SAR to identify species composition.

The SAR map was georeferenced and co-registered with the vegetation map with less than one pixel (30 m) accuracy. The center location of the sites were identified on the images by using the GPS (Ground Positioning System) data. Stand compositions of 19 sites were computed over 5x5 pixels from SAR and vegetation maps. The results in Table 3 indicate that classification of auxiliary sites and tower sites are in good agreement with the field data and the vegetation map. Over 13 forest stands, errors in percentage of each species represented in the classification are less than 8%. The remaining 6 sites are mixed and contain species that are not included in the SAR classification. Over these sites the errors in estimating species composition can increase to 20% with the exception of the auxiliary site G413M where the error exceeded 50%. These errors stem from several factors: 1) the spatial variability of species composition within the mixed stands is not compatible with the pixel sizes of the SAR map, 2) the location of the sites on the SAR map can be wrong due to errors in the GPS measurements that may be larger than 100 m, and 3) the number and size of plots used in the field measurements may not be adequate for the mixed stands. Furthermore, since a combination of tree geometry, biomass and surface conditions contribute in changes of SAR backscatter, the presence of several tree species within one SAR pixel will add to the confusion of the classifier in separating stands. These results suggest that the SAR map can be used to determine the species composition on the scale of SAR image data. Given the fact that SAR classification is performed by assuming that the training areas are purely single species stands, we expect the SAR data have better accuracy in mapping stand composition if the training areas were chosen differently.

Next, we examine the accuracy of the SAR map over the entire modeling grid by computing the percent area covered by each forest type in the region. An area of approximately 25 km x 35 km are taken from the middle of the SAR map and the number of pixels of each forest type is counted and divided by the total number of pixels. In Table 4, the percent area covered by each type in SAR map and vegetation cover map are compared. The difference between the two maps represented by the percentage of change imply a combination of errors in both maps and changes in the land cover between the

time of the two data takes. If the vegetation cover map is considered accurate at the time of the SAR data take, then the difference can mean that 23% of the total area has been classified inaccurately. Field observations during BOREAS campaigns showed that certain parts of the land cover have been altered. For example, some logged and burned areas have been forested and some forest areas have been recently cut. Since there is no accurate information about the land cover types on a regional scale, the assessment of the accuracy of the SAR map can be difficult. Given the uncertainties in vegetation cover map, we expect that on a regional scale, more than 77% of the total area can be classified accurately with SAR imagery.

### *Process Modeling Requirements:*

Land cover maps can be used as one of the parametric inputs to ecosystem process models. The requirements for accuracy and spatial scale of the map depend on the ecosystem model and the application. For example, general circulation models (GCM) have incorporated a 1° by 1° global land cover classification maps [Sellers et al., 1994]. Recently an AVHRR/NDVI based global land cover map has also become available as an input to GCMs (Delrieux and Townshend, 1994). For modeling the net canopy assimilation in boreal or tropical forest, ecosystem models may require much finer resolution data over local or regional scales (Bonan, 1993). The BOREAS process models require five major land cover types for the region. These are conifer-wet, conifer-dry, deciduous, mixed conifer-deciduous, and fen and disturbed. As an attempt to produce maps that can be readily used as input parameters to these models, we combined classes and modified the SAR and vegetation cover maps to represent these five classes. Since over the modeling sub-grid mapped by SAR, pure deciduous and fen sites are rare, we have chosen conifer-wet, conifer-dry, mixed deciduous and conifer, clearing/disturbed, and open water as typical cover types for the region. The new classes are formed by grouping BS, BS/JP, and MX (mixed wet) into conifer-wet, JP in conifer-dry, TA/MX, JP/TA into mixed conifer-deciduous class. The clear cut and disturbed and open water classes are not changed. The results are shown in Figure 6. By preserving the original pixel size (30 m), the new maps can be used in future for the accurate estimation of land use change due to environmental and anthropogenic forces. The modified SAR and vegetation cover maps show similar patterns of land cover types in the region. A comparison of the two images over a 25 km X 35 km sub-area is given in Table 5. Results indicate that the accuracy of the SAR image can improve when fewer classes are used. The difference between the two maps has reduced to only 7.3% of the

total area. This means that by reducing the number of classes to functionally significant land cover types, SAR data can provide maps with greater 92% accuracy over the modeling grid.

## SUMMARY AND CONCLUSIONS

This work summarizes the approach and the results of mapping forest types in the southern study area of the BOREAS project in the boreal forest of Canada by using SAR imagery. The images are collected by the airborne J11, AIRSAR system and combined in a mosaic to cover the ecosystem process modeling sub-grid. Eight classes have been separated in the SAR image and the accuracy of the classification of have been performed at several levels. Over 19 forest stands surveyed during the BOREAS field campaigns, the SAR map exhibited an accuracy of about 90%. The analysis showed that the map was also able to correctly predict tree species composition on the SAR pixel scale. At a larger scale, an area of 25 km x 35 km from the SAR map was compared with a digital vegetation map based on the infrared aerial photography and more than 77% of the total area was classified accurately. Finally, the number of classes were reduced to produce a map compatible with the requirements of the BOREAS land surface process models. The reduced map had 5 classes and when compared with the vegetation map, showed similar land cover patterns with greater than 92% accuracy over the total area. It is important to note that the classification accuracies performed in this study were highly dependent on the accuracy of the image calibration and impediments caused by errors due to incidence angle effects, aircraft motion compensation, and the image mosaic procedure. Furthermore, the results were obtained by using data from a single date. Multi-temporal data can provide information about the seasonal and environmental states of the boreal forest and enhance the characteristics of the feature space for the classifier. Therefore, we believe that the accuracy obtained in this study is conservative and can be improved by incorporating multi-temporal data, and spaceborne systems with better image fidelity.

Some of the important results of the SAR classification were the separation of black spruce and jack pine stands and the coniferous and deciduous trees with close to 100% accuracy. These forest types are considered the dominant coniferous and deciduous stands covering large patches throughout the entire region of the boreal forest. The results have also a significant impact on modeling the canopy assimilation and biogeochemical processes for the region. Deciduous trees, because of their phenological, understory, and seasonal characteristics than conifers, represent different functional forms in ecosystem process models. Among conifers, jack pine and black spruce trees are also

treated differently in process models. Unlike dry and sandy soils of jack pine stands, black spruce patches are often covered with thick moss layer over poorly drained soils and with different characteristics in the release of the trace gases from the soil surface and canopy.

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## Figure Captions

Fig. 1. Map of the BOREAS southern study area and the modeling sub-grid.

Fig. 2. Digital vegetation map of the modeling sub-grid assembled from visual interpretation of infrared aerial photography. The map includes 8 different types of land cover which are regrouped from aboriginal 40 land cover classes.

Fig. 3. P-band polarimetric color overlay of the AIRSAR mosaic image of the modeling sub-grid within the BOREAS southern study area acquired on July 21, 1994. P-band HH, HV, and VV polarizations are respectively colored in red, green, and blue. The mosaic image is co-registered with the digital vegetation map and georeferenced to UTM coordinates with North being parallel to the side of the image.

Fig. 4. Map of forest types obtained from L-band polarimetric, L-band C-band HH and L-band IV polarizations. The map includes 8 classes similar to Fig. 2. The classes are JP (jack pine), BS (black spruce), JP/TA (dominant jack pine mixed with trembling aspen), BS/JP (dominant black spruce mixed with jack pine), TA/MX (dominant trembling aspen mixed with other conifers), MX (mixed conifer), CC (clear cut, bogs, and disturbed), OW (open water).

Fig. 5. Map of forest types obtained over the aspen tower site in the Prince Albert National Park. The map was obtained from a frame image covering an area of approximately 10 x 10 km. The cover types are similar to Fig. 4. with aspen being separated from other land cover types,

Fig. 6. (a) Reduced SAR map over the modeling sub-grid derived from the original SAR map shown in Fig. 4. The map includes 5 classes of conifer-wet, conifer-dry, mixed deciduous and conifer, clear cut, and open water. (b) Reduced digital vegetation map derived from the original vegetation map by regrouping the land cover classes.

Table 1. Radar characteristics of the training sites of forest type classes at P-, L-, and C-band frequencies on July 21, 1995.  $\sigma_{pq}^0$  is the backscattering coefficient at pq polarization averaged over the number of pixels within each training site and  $\phi$  and  $\rho$  are the phase difference in degrees and the coefficient of correlation of hh and vv polarizations respectively.

Frequency	$\sigma_{hh}^0$	$\sigma_{hv}^0$	$\sigma_{vv}^0$	$\phi$	$\rho$	pixels	Class
P-band	-1.13	-12.40	-3.74	69	0.48	2814	JP
	-7.02	-14.65	-6.21	28	0.37	1097	BS
	-4.80	-13.99	-8.24	78	0.25	4920	TA/MX
	-6.66	-17.14	-5.75	51	0.24	1883	JP/TA
	-1.28	-12.33	-0.44	64	0.46	1850	MX
	-6.25	-14.28	-6.58	36	0.20	2006	BS/JP
	-10.24	-22.69	-14.78	8	0.36	1097	CC
	-15.26	-27.71	-14.35	19	0.35	286	OW

Frequency	$\sigma_{hh}^0$	$\sigma_{hv}^0$	$\sigma_{vv}^0$	$\phi$	$\rho$	pixels	Class
L-band	-1.80	-12.35	-6.49	120	0.41	2814	JP
	-5.73	-13.62	-6.75	23	0.36	1097	BS
	-6.69	-12.16	-7.41	32	0.14	4920	TA/MX
	-5.87	-15.47	-7.39	49	0.30	1883	JP/TA
	-2.50	-10.83	-4.01	94	0.26	1850	MX
	-5.07	-13.23	-7.83	63	0.16	2006	BS/JP
	-9.20	-20.32	-12.60	19	0.44	1097	CC
L	-20.21	-29.77	-16.54	2	0.48	286	OW

Frequency	$\sigma_{hh}^0$	$\sigma_{hv}^0$	$\sigma_{vv}^0$	$\phi$	$\rho$	pixels	Class
C-band	-6.47	-13.03	-8.56	4	0.32	2814	JP
	-5.24	-13.05	-7.36	15	0.47	1097	BS
	-7.13	-12.84	-6.38	5	0.047	4920	TA/MX
	-5.98	-13.59	-9.16	11	-0.35	1883	JP/TA
	-4.48	-12.06	-7.08	15	0.32	1850	MX
	-5.74	-12.88	-7.24	12	0.48	2006	BS/JP
	-8.69	-18.38	-11.51	17.5	0.58	1097	CC
	-22.70	-29.75	-21.19	10	0.34	286	OW

Table 2. Confusion matrices of forest types derived from MLE and MAP classifiers. The diagonal elements of confusion matrices define the percentage of those pixels that has been classified into the correct class.

(a) *Maximum Likelihood Classifier*

Species	JP	BS	TA/MX	TA/JP	MX	BS/JP	CC	OW
JP	98	0	1	0	1	0	0	0
BS	0	95	0	4	0	1	0	0
TA/MX	0	0	98	0	1	0	0	0
JP/TA	1	26	2	58	0	13	0	0
MX	6	0	0	0	94	0	0	0
BS/JP	0	13	3	1	0	82	0	0
CC	0	0	0	0	0	0	100	0
OW	0	0	0	0	0	0	2	98

(b) *Maximum-a-posteriori Classifier*

Species	JP	BS	TA/MX	TA/JP	MX	BS/JP	CC	OW
JP	100	0	0	0	0	0	0	0
BS	0	99	0	0	0	1	0	0
TA/MX	0	0	100	0	0	0	0	0
JP/TA	0	20	0	72	0	7	0	0
MX	0	0	0	0	100	0	0	0
BS/JP	0	0	0	0	0	100	0	0
CC	0	0	0	0	0	0	100	0
OW	0	0	0	0	0	0	2	98

Table 3. Tree species composition of 19 forest stands in the modeling sub-grid area. The ground truth data was taken from the field notes of TE-6 investigators (Sellers, et al., 1995). WS is white spruce (*Picea glauca*). Lala is *Larix laricina*, Abba id Balsam Fir (*Abies balsamea*), Bepa is paper birch (*Betula papyrifera*). Numbers in ground truth column indicate the percentage of each tree species based on the number of stems within the test plots. In vegetation cover and SAR maps, the numbers indicate the percentage of image pixels of each stand classified in type of forest.

Site	Stand Composition 1 (Ground Truth) %	Stand Composition 2 (Cover Map) %	Stand Composition (SAR Map) %
G2L7S	BS: 40, Lala: 60	BS: 99, JP/BS: 1	BS: 64, MX: 36
G9I4S	BS: 99, Salix: 1	BS: 100	BS: 100
G2I4S	BS: 92, TA: 2, Salix: 2, Bepa: 3	BS: 100	BS: 96, JP: 4
G6K8S	BS: 94, lala: 6	BS: 100	BS: 100
F1N0M	TA: 71, WS: 25, Abba: 3	TA/JP: 92, BS: 8	TA/MX: 96, JP: 4
G8L6P	JP: 91, TA: 9	JP/TA: 100	JP: 76, JP/TA: 8, BS/JP: 16
F5I6P	JP: 100	JP: 100	JP: 92, TA/MX: 8
G9L0P	JP: 100	JP: 100	JP: 100
F7J0P	JP: 17, WS: 4, BS: 74, TA: 4	BS: 100	BS: 96, JP: 4
F7J1P	JP: 59, BS: 17, TA: 23	JP/TA: 72, TA: 16, BS: 12	JP: 60, TA/MX: 24, MX: 16
G4K8P	JP: 100	JP: 100	JP: 100
G1K9P	JP: 100	JP: 100	JP: 96, BS/JP: 4
G7K8P	JP: 100	JP: 100	JP: 100
G4I3M	TA: 49, WS: 43, Bepa: 6, Abba: 3	TA/WS: 96, WS/TA: 4	TA/MX: 20, BS/JP: 68, JP: 12
TE-OBS	BS: 100	BS: 100	BS: 100
TE-OJP	JP: 100	JP: 100	JP: 100
TF-YJP	JP: 100	JP: 84, JP/TA: 16	JP: 64, JP/TA: 36
ADM-3		TA/JP: 92, JP/TA: 8	TA/MX: 92, JP/TA: 8
BDH-4		JP/TA: 76, BS: 24	TA/MX: 20, JP/TA: 68, MX: 12

Table 4. Area percentage of land cover types over 875 km<sup>2</sup> of modeling sub-grid derived from original SAR and vegetation cover maps. The change shows the percentage of difference of SAR map in areas of land cover types from the cover map.

Cover type	SAR Map %	Cover Map %	Change %
JP	18.26	17.73	+ 0.53
BS	30.27	37.79	- 7.52
TA/MX	8.17	7.86	+ 0.31
JP/TA	5.73	10.01	- 4.28
MX	16.36	8.39	+ 7.97
BS/JP	15.57	12.91	+ 2.66
CC	3.62	3.39	+ 0.23
OW	1.23	1.59	- 0.36

Table 5. Area percentage of land cover types over 875 km<sup>2</sup> of modeling sub-grid derived from reduced SAR and vegetation cover maps.

Cover Type	SAR Map %	Cover Map %	Change %
Conifer-Wet	62.22	59.34	+ 2.88
Conifer-Dry	18.27	17.73	+ 0.54
Deciduous/Conifer	13.91	17.22	- 3.31
Disturbed/Bog	3.62	3.39	+ 0.23
Open Water	1.23	1.59	- 0.36

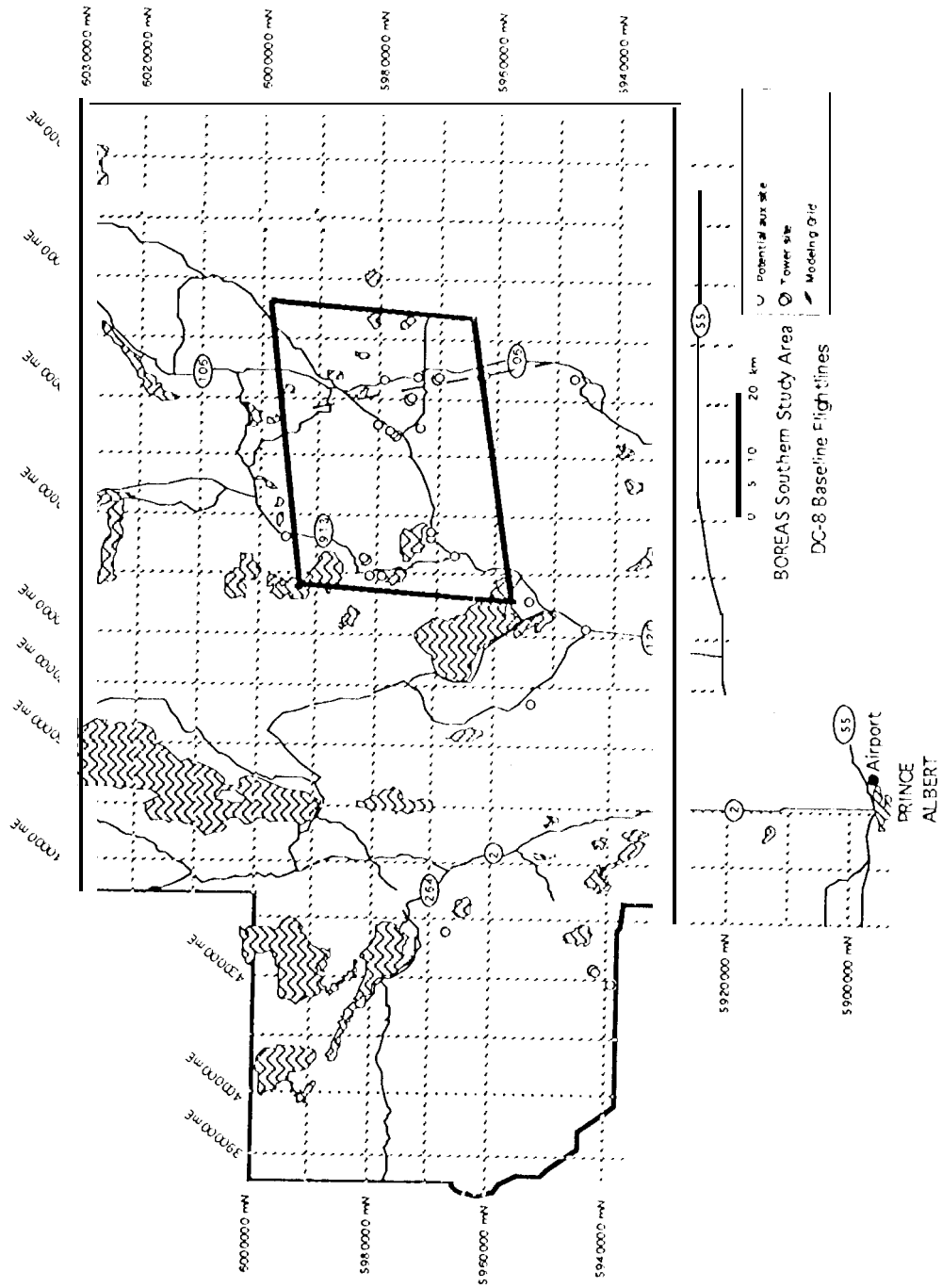


Figure 1

IR LAND COVER MAP



JP BS JP/TA BS/JP TA/MX MX CC OW



AIRSAR MOSAIC, BOREAS, JULY, 1994



RED: P-HH

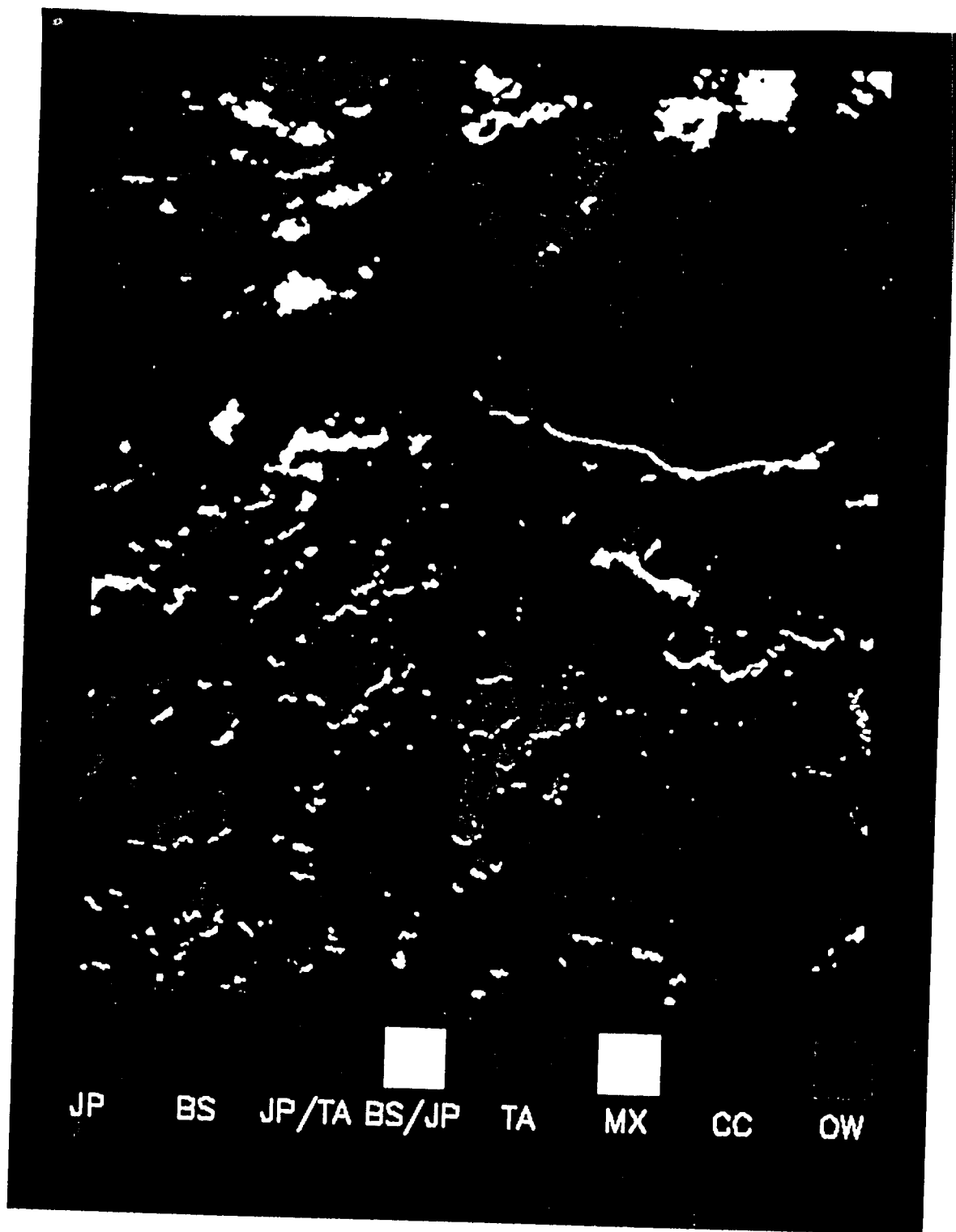
GREEN: P-HV

BLUE: P-W

0 5 km

AIRSAR LAND COVER MAP





AIRSAR MAP



(a)

CONIFER-DRY

CONIFER-WET

DECIDUOUS/CONIFER

CLEARCUT/BOG/FEN/NONPRODUCTIVE

OPEN WATER

VEGETATION MAP



(b)